

Demystifying AI: WHAT DIGITAL TRANSFORMATION LEADERS CAN TEACH YOU ABOUT REALISTIC ARTIFICIAL INTELLIGENCE

California Management Review
1–25© The Regents of the
University of California 2019

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DOI: 10.1177/1536504219865226

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SUMMARY

Recent years have seen a reemergence of interest in artificial intelligence (AI) among both managers and academics. Driven by technological advances and public interest, AI is considered by some as an unprecedented revolutionary technology with the potential to transform humanity. But, at this stage, managers are left with little empirical advice on how to prepare and use AI in their firm's operations. Based on case studies and the results of two global surveys among senior managers across industries, this article shows that AI is typically implemented and used with other advanced digital technologies in firms' digital transformation projects. The digital transformation projects in which AI is deployed are mostly in support of firms' existing businesses, thereby demystifying some of the transformative claims made about AI. This article then presents a framework for successfully implementing AI in the context of digital transformation, offering specific guidance in the areas of data, intelligence, being grounded, integrated, teaming, agility, and leadership.

KEYWORDS: artificial intelligence, polls and surveys, managers, management, management skills

In 2014, Dr. Julio Mayol wondered, “We have access to a vast quantity of data but it’s hard to extract meaningful information that helps us improve the quality of the care we provide.” Dr. Mayol, Medical Director and Director of Innovation at the Carlos Clinical Hospital in Madrid, Spain, founded in 1787, found the answer after consulting with an external group of technology advisors: artificial intelligence (AI). About six months later, the innovation unit of the hospital, under his leadership, embarked on a project to apply AI. Rather than opting for an off-the-shelf generic solution, the team worked closely with a technology

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provider of AI solutions and co-created an innovative new AI application tailored to their specific needs. After one year, the system was ready for field testing. Six months later, first results showed that the diagnostic and patient's risks assessment solution can cut the time in half for preliminary assessment of patient records, with a 95% accuracy compared with eight domain experts who were psychiatrists with more than 20 years of experience. An unanticipated positive side effect of this immense increase in efficiency was that the medical staff had much more time for consultations and patient care, thereby increasing customer satisfaction.¹

This exemplary case of a successful AI² application stands in stark contrast to mounting evidence of AI failures,³ gaps between firms' AI ambition and execution,⁴ and a general "post-AI-hype sobering."⁵ Given the mixed evidence and the paucity of empirical insights related to the successes and failures of AI implementation projects, we embarked on a global research project with the aim of understanding managers' perceptions and evaluations of AI. This research was informed by insights derived from the opening case as well as publicly available case study material.⁶ All these cases were excluded from the survey investigation. Between 2016 and 2018, more than 3,000 executives and managers were surveyed globally from across industries with a total of nearly 7,000 projects, including the application of AI and other advanced digital technologies. We do not necessarily assume that managers know best, but they are important information sources about current and future AI potential for various reasons. First, given their involvement and business interest, they are the decision makers about future projects. Second, their perceptions and experiences will influence future implementation success.

Based on the above assessment (with high expectations and a few success stories on the one side, but frustrating experiences and stopped projects on the other side), we first establish the current prevalence of AI in business (study 1) and then explore key dimensions of successful AI implementations (study 2). Specifically, study 1 focused on the following research question (RQ1; see Figure 1):

Research Question 1 (RQ1): To what extent has the application of AI diffused in business?

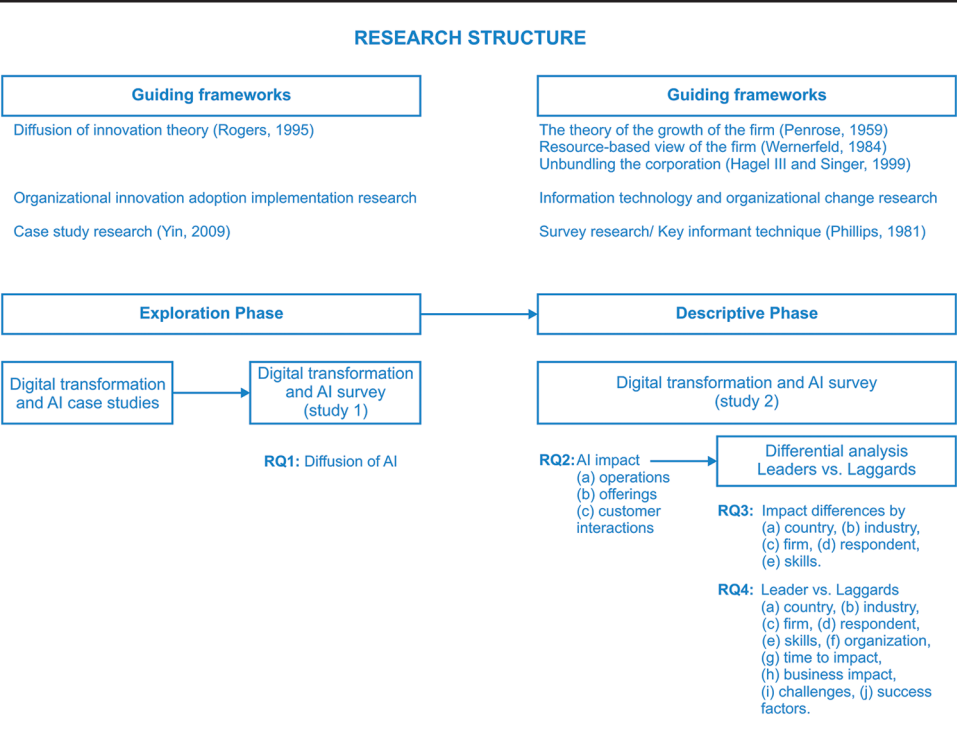
In study 2, we explored AI in business in more detail. Specifically, we were interested in the following three research questions (RQ2-RQ4; see Figure 1):

Research Question 2 (RQ2): What are the anticipated perceived business impacts of AI? More specifically, to what extent are managers expecting impacts in the area of operations, offerings, and customer interactions?⁷

Research Question 3 (RQ3): Assuming differences concerning the perceived business impact of AI, what explains those differences, for example, on a country, industry, firm level, executive (respondent), and skill level?

Research Question 4 (RQ4): Given the opening case of AI success, can we identify leaders, firms that are experienced and successful in

FIGURE 1. Structure and guiding frameworks of the research.



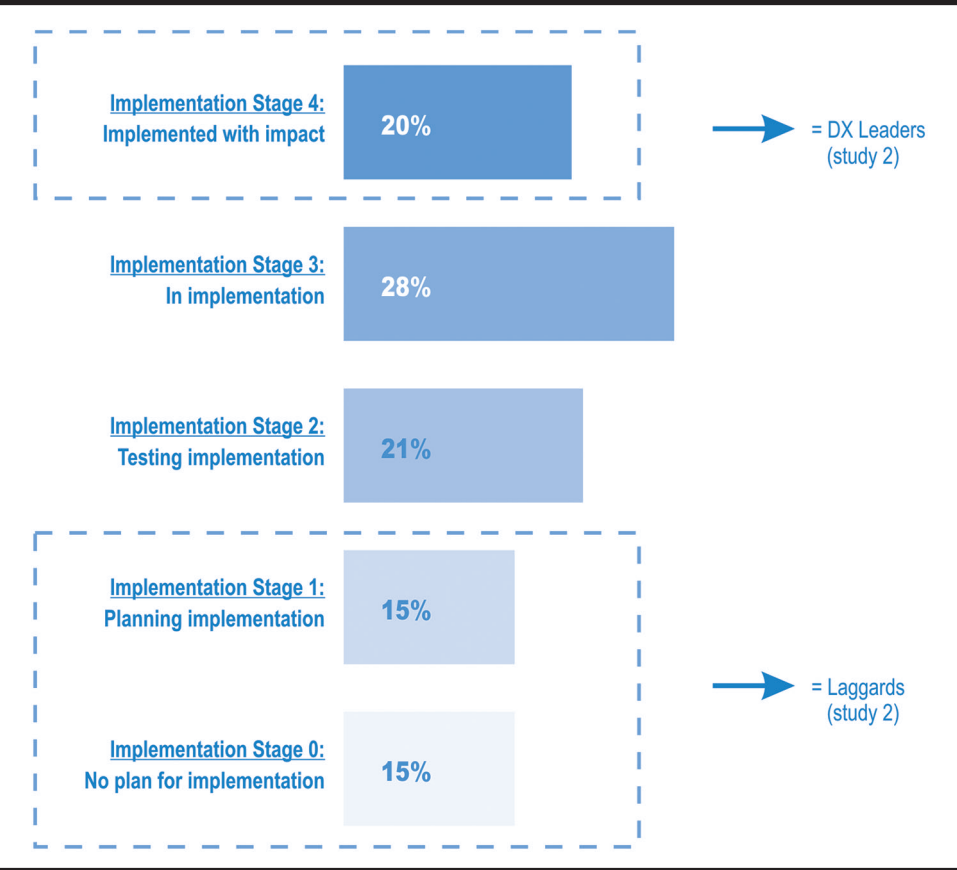
Sources: Framework references (in alphabetical order): John Hagel III and Marc Singer, “Unbundling the Corporation,” *Harvard Business Review*, 77/2 (March/April 1999): 133-141; E. T. Penrose, *The Theory of the Growth of the Firm* (London: Wiley, 1959); Lynn W. Phillips, “Assessing Measurement Error in Key Informant Reports: A Methodological Note on Organizational Analysis in Marketing,” *Journal of Marketing Research*, 18/4 (November 1981): 395-415; Everett M. Rogers, *Diffusion of Innovations*, 4th ed. (New York, NY: The Free Press, 1995); B. Wernerfeld, “A Resource-based View of the Firm,” *Strategic Management Journal*, 5/2 (April-June 1984): 171-180; Robert K. Yin, *Case Study Research: Design and Methods*, 4th ed. (Los Angeles, CA: Sage, 2009).

implementing AI-related projects?⁸ What makes them different from lag-gards, firms that have not yet moved beyond the planning phase, in terms of country-, industry-, firm-level factors, executive (respondent) factors, skills, and organizational traits? Furthermore, could these leaders realize more positive business impacts in areas such as operational efficiency, organizational agility, revenue growth, competitiveness, and customer experience? And how long does it usually take from the start of an AI project to achieving business impacts? In addition, we investigate whether leaders differ in their perception of AI implementation challenges and key success factors.

Research Structure and Guiding Frameworks

Figure 1 illustrates our research structure and the guiding frameworks we used. Phase 1 of our research, the exploration phase, was informed by initial case study research (e.g., the opening case) and a first digital transformation

FIGURE 2. Status of AI implementation in firms (study 1).



Source: We derived these five stages from interviews with managers and the organizational stages-of-innovation-adoption-implementation literature (e.g., G. W. Downs Jr., and L. B. Mohr, “Conceptual Issues in the Study of Innovations,” *Administrative Science Quarterly*, 21/4 (December 1976): 700-714; M. A. Scheirer, “Approaches to the Study of Implementation,” *IEEE Transactions on Engineering Management*, 30/2 (1983): 76-82; L. G. Tornatzky and B. H. Klein, “Innovation Characteristics and Innovation Adoption-implementation: A Meta-analysis of Findings,” *IEEE Transactions on Engineering Management*, 29/1 (1982): 28-45; Everett M. Rogers, *Diffusion of Innovations*, 4th ed. (New York, NY: The Free Press, 1995).

Note: n = 1,614 firms, worldwide, 2016-2017: “Which best describes the progress of your firm’s AI (Artificial Intelligence) implementation?” AI = artificial intelligence; DX = digital transformation.

and AI survey that aimed at understanding the extent of AI diffusion across firms worldwide. Given that AI is a recently adopted technology for most firms, this stage of our research was informed by diffusion of innovation theory in general and organizational innovation adoption implementation research in particular. From this body of past research, plus managerial interviews, we developed our stages of AI implementation model (see Figure 2). Phase 2 of our research, the descriptive phase, aimed at a broad yet deeper understanding of AI in firms’ digital transformation worldwide. As the differential analysis emerged in phase 2 of our research, this phase was guided by three related organizational frameworks: the theory of the growth of the firm, the resource-based view of the firm, and the pragmatic firm conceptualization proposed by Hagel and Singer.⁹ All three have

an internal resources focus in common and have guided our assessments in terms of firms' experience, capabilities, challenges, and success factors. As a multistage, mixed-methods research design, research phase 1 informed research phase 2.

Data Collection

Data for this study were obtained in two waves (see Figure 1). Following a set of digital transformation AI case studies, the first exploratory survey was conducted in 2016-2017, addressing the first research question. The survey was conducted globally, online, utilizing a database of executives and senior managers provided by an international market research firm. The second survey was conducted in 2017-2018, addressing RQs 2 to 4. The second survey used a similar methodology. It was conducted globally, online, and the same market research firm provided samples of executive respondents. Sampling was guided by the following:

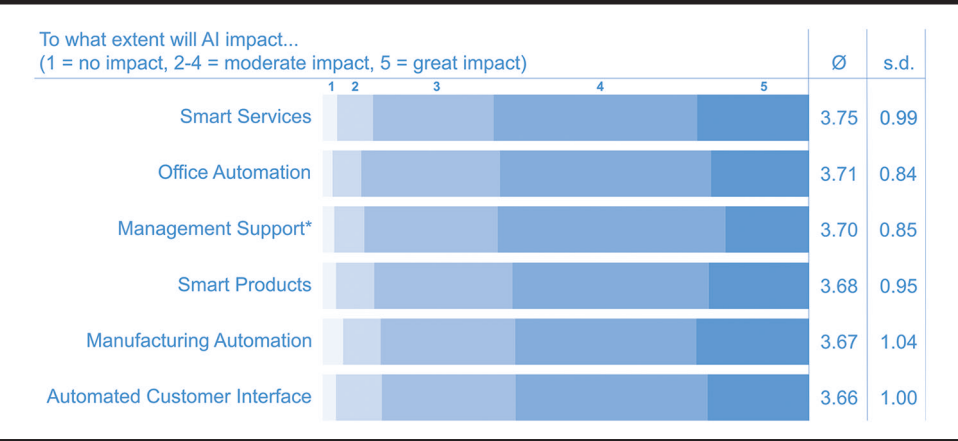
- Global coverage: firms from key countries (in terms of economy/GDP) in the Triad.¹⁰
- A minimum country quota of $n = 50$ where possible (with the exception of New Zealand with $n = 29$ in study 2, this was achieved).
- North American Industry Classification System (NAICS) industry sampling: focus on manufacturing (NAICS code 23, 31, 32, 33), information (NAICS code 51), transportation (NAICS code 48, 49), retail (NAICS code 41, 42, 44, 45), financial services (NAICS code 52), healthcare (NAICS code 62).
- Minimum industry quota: $n = 50$.
- Focus on medium to large firms in terms of revenue and employees.
- Senior respondents: focus on key informants of firms at C- or VP-level or above.

In order to assess response bias, we followed the logic of Armstrong and Overton¹¹ and found no statistically significant differences at the .05 level in regard to any of the variables that we are reporting below. In terms of common method bias, we applied the marker variable approach and found no significant effects.¹² Overall, we are confident that our findings can be generalized to medium to large Triad enterprises in the industries sampled and that our results are not the result of the instrument/sample used in our analysis. Sample details are provided in the endnote.¹³

AI in Business

To what extent are firms already using AI in their business? In 2016-2017, the time of the first survey, AI applications had already diffused quite broadly, with only 15% of firms not yet having any AI plans and 20% already having delivered results (see Figure 2).

FIGURE 3. Anticipated DX/AI impacts on business (study 2).*Note:* $n = 1,218$ firms, worldwide, 2017-2018: “In terms of business impact of AI, to what extent will AI make an impact in each of following areas?”



Note: AI = artificial intelligence.
*Knowledge management refers to decision-making and knowledge management support.

Interestingly, the application of AI was typically an integral part of a firm’s digital transformation project. With the exception of isolated experimentation with specific AI techniques such as deep learning, AI was not used in isolation, but as one technological element of several technologies aimed at enhancing a firm’s present and future business.¹⁴ It emerged that digital transformation is often the context for AI projects, such as call center transformation using advanced analytics and AI or transforming operations using Internet of things (IoT), advanced analytics, and AI.

The Business Impact of AI

In the second survey, which was executed in 2017-2018, we built on the insights from the first survey and explored the role of AI in firms more deeply. What are the anticipated perceived business impacts of AI? AI can impact the internal operations of a firm, its offerings (in the form of smart products and services¹⁵), and how it interacts with its customers. The survey data largely confirm this (Figure 3). The surveyed executives foresee AI to impact their firms’ offerings. More specifically, they foresee AI to impact the creation of smart services, to automate operations and manufacturing, to support decision-making and knowledge management, and to automate customer interfaces. Interestingly, the strength of the anticipated impacts does not vary too much (average range: 3.7-3.8 on a 5-point scale). This we interpret as the typical fairly undifferentiated perception by businesses of a new technology prior to wider and deeper diffusion and the emergence of standard business cases and applications.

Despite the largely undifferentiated perception of AI’s business impact—the perception of AI business impacts was also largely similar across countries and industries—some differences emerged. The impact on smart services is *more*

pronounced in financial services and *less* in healthcare, and the impact on manufacturing is more pronounced in the manufacturing sector. However, these significant differences only exhibited effects that are rather small.¹⁶

While, on average, AI's anticipated business impact is seen as moderate to high across all the business impact categories investigated, 3% of the ratings anticipate no impact and 21% anticipate a high impact.¹⁷ What explains those differences?

Of the 10+ factors at the country, industry, firm, and executive (respondent) level we examined,¹⁸ only digital skills have a strong impact. Firms with stronger digital skills anticipate stronger AI-induced business impacts compared with firms with weaker digital skills. This observation is stable across industries and regions (see Figure 4).

These digital skills comprised four, interrelated organizational capabilities:

- Strategic capabilities: digital strategy and digital business development skills.
- Technology capabilities: skills in new digital technologies such as AI or IoT.
- Data capabilities: data science skills.
- Security capabilities: cybersecurity skills.

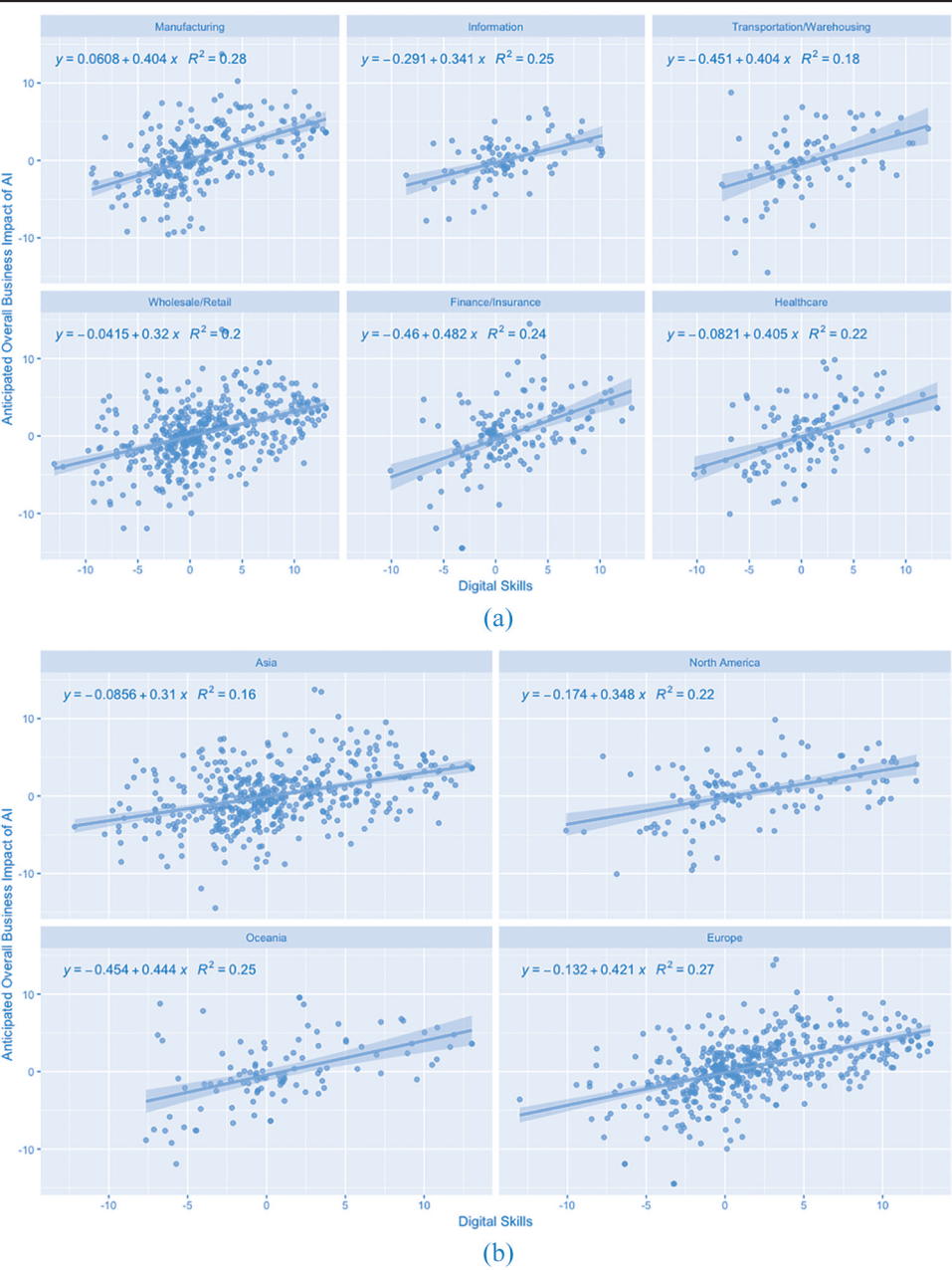
These results suggest that, just like with other technological innovations in the past, to realize the potential of the new digital technology, AI requires specific organizational capabilities as the firm and the new technology align for best application and impact.¹⁹ AI requires new information technology (IT) skills that are both AI-specific, such as machine learning skills, and generic, such as understanding of modern programming languages (e.g., Python), application development techniques (e.g., agile software development), and modern IT architecture skills (e.g., edge computing).²⁰ In addition, data management and analytical skills are required. AI thrives on massive amounts of data requiring the existence of digital data, its management, and its analysis and synthesis. Given that most data are network generated (e.g., websites, sensor data from IoT devices), security skills—generic as well as AI-empowered—become vital to ensure access rights, intrusion detection, and data integrity.²¹ Last, these skills have to be embedded in a coherent and suitable strategic framework to ensure a guided implementation and wider organizational alignment and support.²²

We find that firms that have already implemented and delivered business outcomes through three or more digital transformation projects (stage 4; see Figure 2) exhibit particularly strong digital capabilities.²³ These firms we label digital transformation leaders (DX leaders for short); this group consists of about 8% of all firms surveyed.

Digital Transformation Leader Analysis

What makes these digital transformation (DX) leaders different? In order to find out, we compared them with those firms in our sample that either had

FIGURE 4. Anticipated business impact of AI and firms' digital skills (a) across industry (study 2)^a and (b) across regions (study 2)^a.



Note: AI = artificial intelligence.
^aAnticipated business impact and digital skills based on separate summated scales, combining the individual impact and skills items.

no plans yet or were still in the planning phase (implementation stage 0 and 1; see Figure 2). We term these firms “laggards.” Following this classification, we compared 114 DX leaders with 424 laggards. We examined organizational traits

in the area of strategy, leadership, data management, agility, organizational processes, and innovation, as well as country-, industry-, and firm-level factors.

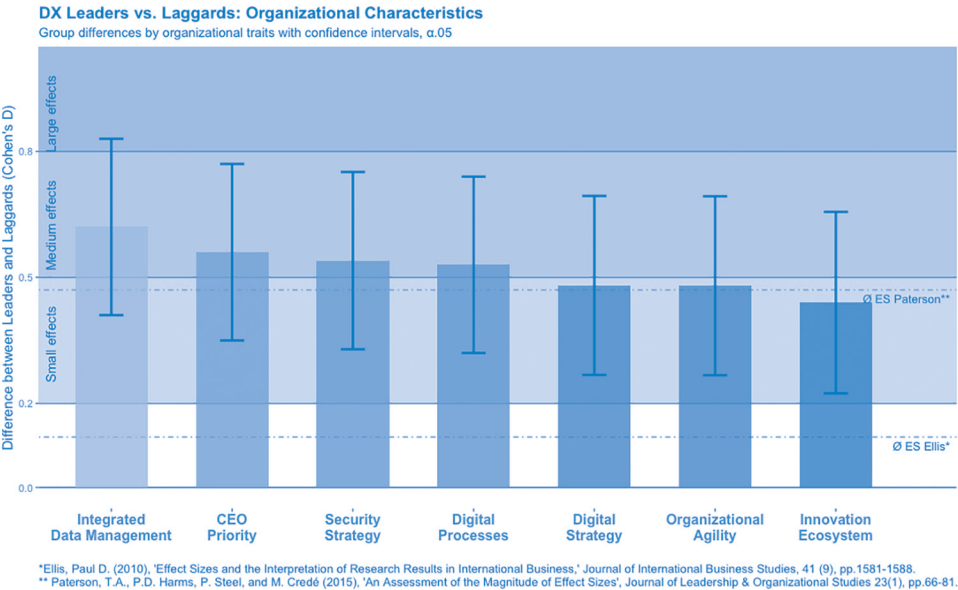
The DX leaders we identify came from across all countries surveyed and are as prevalent among traditional firms as among digital natives.²⁴ They also did not differ significantly with regard to the reported duration from project start to business impact.²⁵ The weak industry differences we observe are a reflection of the different extent of digital transformation initiatives in the industries surveyed, with financial services leading and healthcare lagging.²⁶ With regard to traditional organizational measures (such as size in revenue or the number of employees), DX leaders tend to be larger. They report higher revenues and more employees, but these differences are not very pronounced.²⁷ Besides their noted stronger digital capabilities, we identify organizational characteristics where these leaders excelled.

Organizational Characteristics

When compared with laggards, DX leaders differ significantly and strongly²⁸ in seven organizational traits. In order of size of the difference (effect size) between the two groups, these were integrated data management, CEO priority, security strategy, digital processes, digital strategy, agility, and open innovation ecosystem.

Integrated data management, the most pronounced difference between leaders and laggards, refers to the organizational capability of managing customer and organizational data in a holistic and integrated fashion, avoiding data silos and incompatible data formats. This aspect goes hand in hand with AI's dependence on data. *CEO priority* refers to a firm's leader prioritizing and leading the firm's digital transformation efforts, which include the application of advanced digital technologies such as AI. An organization-wide *security strategy* refers to the definition and execution of a cybersecurity strategy across the whole organization. Given the importance of data, a strategic approach to data security—including the management of access rights, intrusion detection, and disaster recovery mechanisms—is critical. *Digital processes* refer to the digitalization of a firm's core processes such as sourcing, production, performance reviews, or travel management and expense claims. Digital processes are often the outcome of digital transformation projects. Organization-wide *digital strategy* refers to the development and execution of a strategic approach to digital transformation, an approach that is contrasted to unplanned or tactical approaches. Organizational *agility* refers to a firm's ability to rapidly and flexibly respond to customers' needs, adapt production/service delivery to demand fluctuations, and implement decisions in the face of market changes. Agile organizations continuously search for ways to reinvent or redesign their organization and they can do so in a fast and flexible manner as they learn and adapt in the process. *Innovation ecosystem* refers to the establishment of an open ecosystem for innovation, beyond the boundaries of the firm. Such ecosystems tie into the resources, capabilities, and strength of a firm's network of business relationships, such as ties with suppliers, alliance partners, and customers (Figure 5).

FIGURE 5. Organizational characteristics of DX leaders (study 2).



Note: $n = 538$ firms (114 leaders, 424 laggards), worldwide, 2017-2018: “To what extent do you agree with the following statements?” (from 1 = *strongly agree* to 5 = *strongly disagree*; statements randomly rotated): (1) Digital transformation is the top priority of our CEO; (2) We are executing an organization-wide digital transformation strategy; (3) We have achieved organizational agility; (4) We have established an open ecosystem for innovation; (5) We have digital business processes; (6) We are managing customer and organizational data in an integrated manner; (7) We are executing an organization-wide cybersecurity strategy. DX = digital transformation.

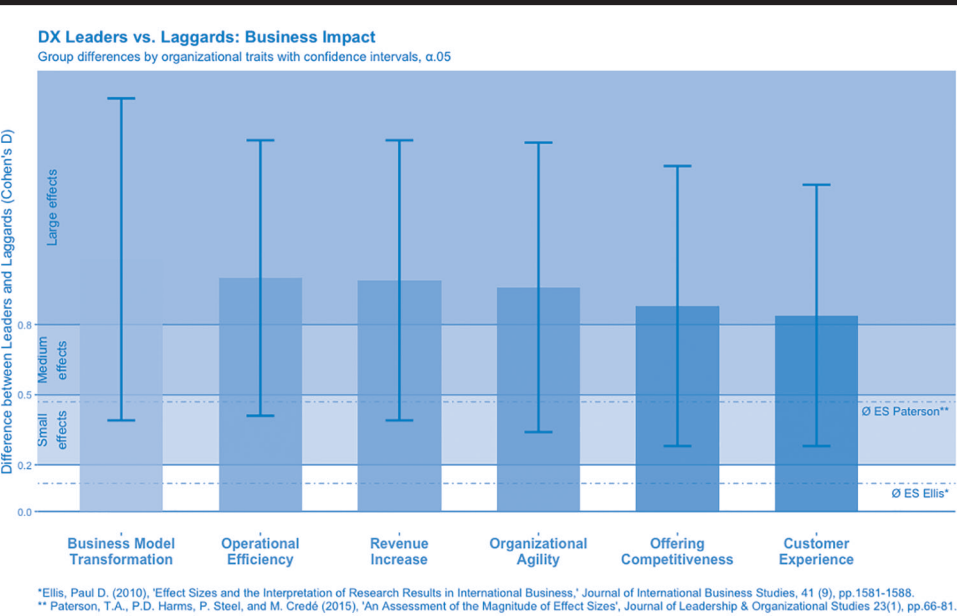
Business Impact

The seven organizational aspects enable the leaders to achieve much greater business impacts compared with laggards. Leaders report significantly stronger actual business impacts in their projects compared with laggards. We find significantly higher levels of impact on transformations of existing business models, improvements in operational efficiency, increase in revenue, strengthening of offerings’ competitiveness, and customer experience enhancements. All of the observed differences are strong (see Figure 6). This moves beyond the mere anticipation of business impact (Figure 3) to managers’ perception of real business impacts actually achieved.

Challenges

Reflecting the importance of digital skills, the main challenge for all firms is lack of skilled staff and knowledge in digital technologies, which was mentioned as an implementation challenge by more than half of the firms combined. Lack of organizational agility, internal resistance to change, security risks, lack of leadership and sufficient funding, as well as the challenge of integrating new digital technology with existing technology were stated as challenges by about a quarter of the firms each. Unavailability of suitable technology partners and

FIGURE 6. DX/AI business impact (study 2).

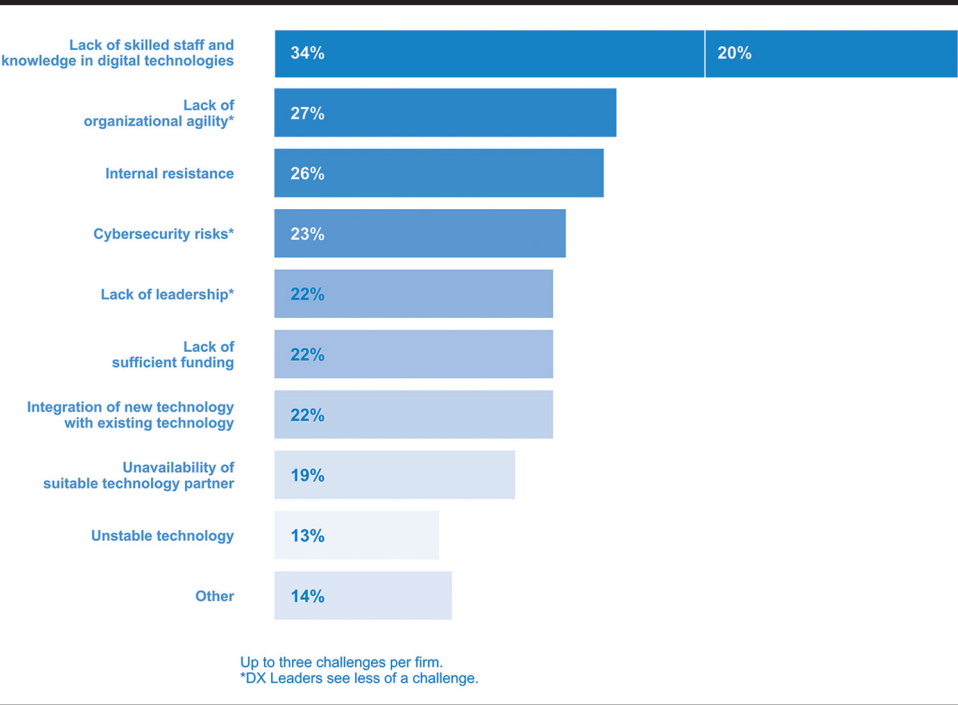


Note: $n = 538$ firms (114 leaders, 424 laggards), worldwide, 2017-2018: “To what extent have you delivered outcomes specified in each of following statements?” (from 1 = *not at all* to 5 = *to a great extent*; statements randomly rotated): (1) Increase in revenue; (2) Improvement in customer experience; (3) Strengthening of competitiveness of products or services; (4) Efficiency improvements; (5) Improvement of business agility; (6) Transformation of business models. AI = artificial intelligence.

unstable technology are mentioned as challenges by 19% and 13% of firms, respectively (Figure 7).

Contrary to our expectations, we uncover few differences in terms of challenges perceived by leaders versus laggards. Only organizational agility, security risks, and lack of leadership were challenges that the leaders did perceive as *less* of a challenge in their AI projects. However, the effect of these differences was fairly small.²⁹ We interpret this rather surprising finding as follows. Although the barriers or challenges that firms perceive are similar, the DX leaders have more experience and a stronger resource base to overcome them. This becomes most obvious when looking at the three challenges the DX leaders perceived as significantly less of a challenge and comparing those with challenges that are perceived similar. For example, lack of leadership: DX leaders stated lack of leadership significantly less often as an implementation barrier compared with laggards. Given that DX leaders had significantly more CEOs prioritizing digital transformation, perceptions of lack of leadership support should be lower. On the contrary, both DX leaders and laggards perceive lack of skilled staff as a key barrier. This is despite the finding that DX leaders have a stronger digital skills resource base. Taken together, this points to the view that perceived challenges are similar, but that in some cases (e.g., lack of leadership), the DX leaders have already developed to a degree that the challenges are less of an actual implementation success barrier compared with the laggards.

FIGURE 7. DX/AI implementation challenges (study 2).



Note: $n = 3,557$ answers by 1,218 firms, worldwide, 2017-2018: “Which of the following statements describes your key challenges? Please select up to three” (categories randomly rotated): (1) Lack of skilled staff*; (2) Lack of knowledge of digital technology*; (3) Lack of organizational agility; (4) Lack of leadership; (5) Fear of change or internal resistance; (6) Unavailability of a right technology partner; (7) Lack of funds; (8) Integrating digital technologies with existing IT; (9) Cybersecurity risks; (10) Adoption of digital technology too early, before it is robust and stable; (11) Others. AI = artificial intelligence; IT = information technology.

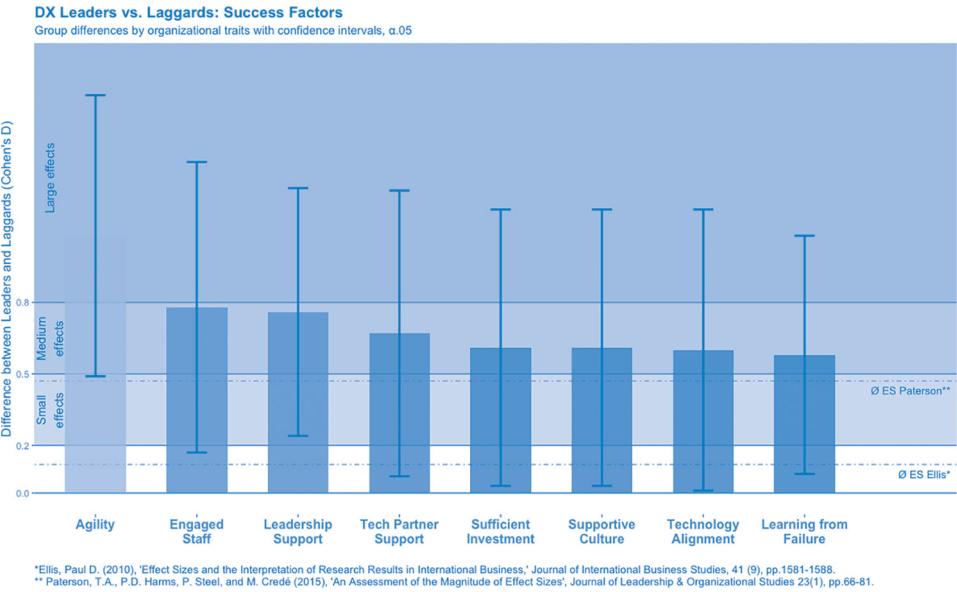
*Combined in the figure.

Success Factors

In contrast to the implementation challenges, which were similar across the firms surveyed, leaders differed compared with laggards in terms of the importance they attributed to factors contributing to digital transformation outcome success. The following eight success factors turn out to be significantly different among the AI leaders: organizational agility, engagement of skilled staff, leadership, support from technology partners, investment, culture, alignment of new digital technologies with existing IT, and learning from failed projects.

The biggest difference between the leaders and the laggards is organizational agility. Leaders attribute much more importance to organizational agility as a factor of project success. Second, leaders have more engaged staff with the required digital skills and leadership support. Support from technology partners, sufficient funding, a supportive culture, alignment of new digital technologies with a firm’s existing technology, and learning from failure were also rated much higher as contributing factors of project success by the leaders as compared with the laggards (Figure 8).

FIGURE 8. DX/AI success factors (study 2).

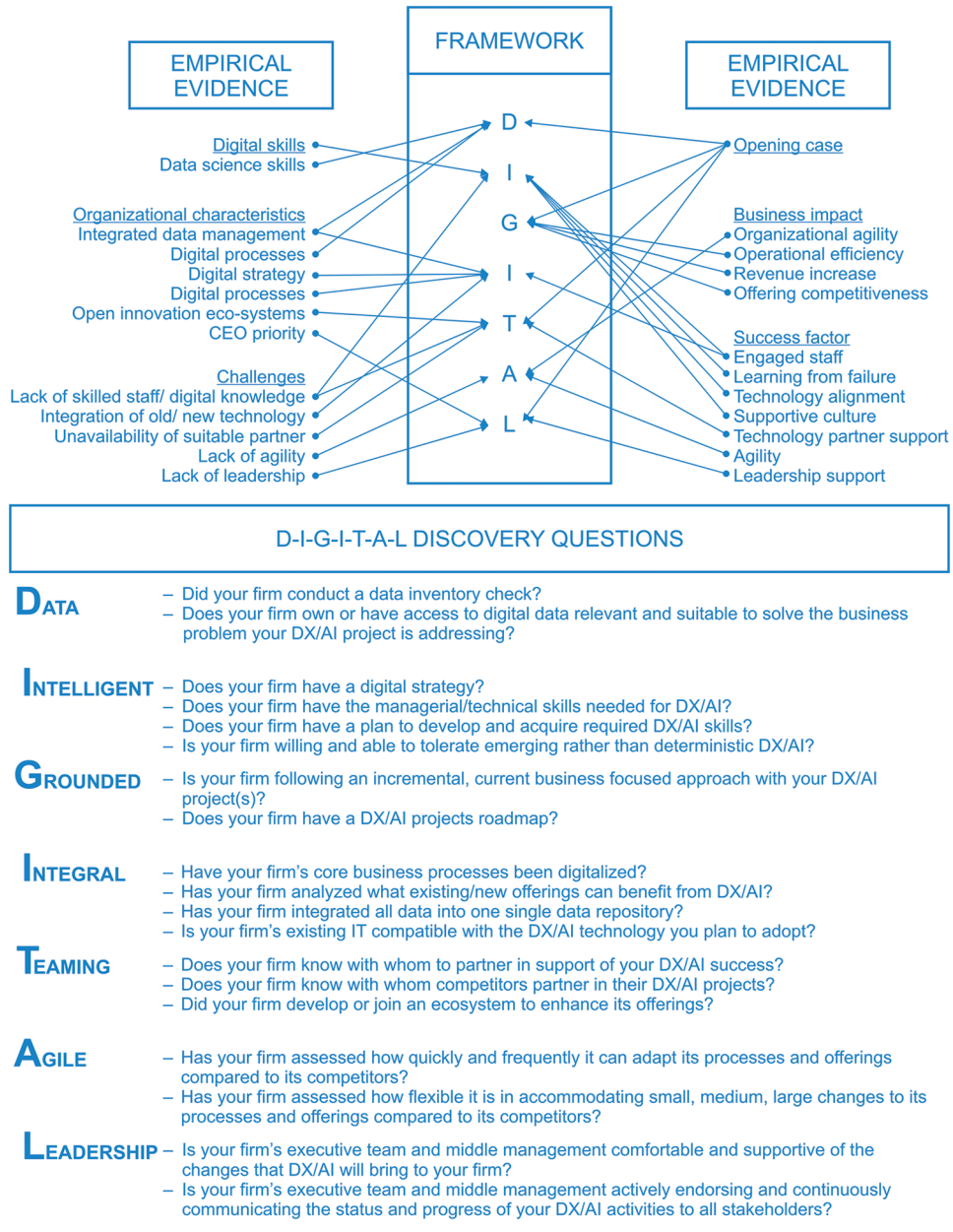


Note: $n = 538$ firms (114 leaders, 424 laggards), worldwide, 2017-2018: “To what extent have the following factors contributed to the overall outcomes you reported?” (from 1 = *not at all* to 5 = *to a great extent*; statements randomly rotated): (1) Engagement of skilled staff; (2) Having the right organization and processes; (3) Leadership by management; (4) Development of an enabling culture; (5) Support from technology partners; (6) Investment by the business; (7) Alignment of new digital technologies with existing IT; (8) Learning from failed projects. AI = artificial intelligence; IT = information technology.

DIGITAL: Guidelines for Successful AI Applications

The present research departed from the tension between AI success stories on one hand and failures and frustrations on the other hand. Based on our research, we now identify seven areas for managerial action and implementation. We use the acronym “D-I-G-I-T-A-L” to describe our implications, where “D” stands for data, “I” for intelligence, “G” for grounded, “I” for integral, “T” for teaming, “A” for agile, and “L” for leadership. We explore these areas below. The more DIGITAL a company is, the higher the likelihood that their digital transformation-embedded AI projects will succeed. For easier comprehension, Figure 9 illustrates the links between the empirical evidence presented and the elements of the DIGITAL implementation framework. Some of the conclusions that we draw from our analyses, obviously, refer to other change projects within the digital transformation of companies as well. With DIGITAL, we also give credit to this notion and remind that implementation of AI, in its present condition, is typically linked to digital transformation of corporations in general. For each of the elements of DIGITAL, we provide managers with a few action-inducing discovery questions in order to guide their AI applications. Answering any of those questions with a clear “No” should alert managers to act accordingly (see Figure 9).

FIGURE 9. Proposed AI implementation success framework, empirical evidence, and action-inducing discovery questions.



Note: AI = artificial intelligence.

Data

Just like Dr. Mayol alluded to in his opening quote, the fundamental basis for AI success is data. AI requires data, digital data, and in high quality. The AI machine learning technique of deep learning is particularly data hungry. For

example, Google needed some 10 million images to teach its Google brain system to identify human faces, human bodies, and cats.³⁰ In a more recent application, the number of images used increased to 300 million images.³¹ Without data available for training, AI cannot create value for firms, and without skills to acquire, manage, and analyze the data, valuable and actionable insights cannot be generated. Our research confirms this. Firms with strong data capabilities are expecting to derive more value from AI, and our DX leader analysis showed that integrated data management practices and digital processes, which generate digital data, separate the leaders from the laggards significantly and strongly.

Managers are, therefore, advised to start with a data inventory check before embarking on AI projects. The data inventory check should address questions such as “Do we own or have access to data that are relevant to analytically solve the business problem we are addressing?” “Are the data available in the right digital format?” “Are the data sets sufficiently large to be efficient and effective?” “Are the data sufficiently complete, consistent, accurate, and timely?”

Be Intelligent

Data are the necessary foundation for AI success, but data alone are not sufficient. We identified lack of skilled staff and knowledge in digital technologies as the top AI implementation challenge and engaged skilled staff as one of the key AI implementation success factors. Therefore, managers need to develop digital intelligence in the form of suitable human skills within their organization. This intelligence extends beyond the necessary data-related data science skills to include the strategic-, technological-, and security-related capabilities that we discussed earlier. In fact, AI requires organizations to develop *human* intelligence. How shall managers develop this intelligence, especially considering that AI-specific technical talent is scarce?³²

First, it is important to realize that AI success is not just a function of technical skills such as data science capabilities and skills in new digital technologies and cybersecurity. Managerial skills in the form of strategic capabilities are vital. Our results showed that firms with stronger capabilities in the area of digital strategies and digital business development skills are expecting to derive more value from AI compared with firms with a weaker skills base. At the heart of these managerial skills is awareness and understanding. This implies awareness of the possibilities and requirements of AI and related new digital technologies and an understanding of how to best leverage this technology in the idiosyncratic context of the firm. Questions such as “How can AI help defend, grow, or transform our business?” or “How can AI improve operational efficiencies?” are indicative. Answering such questions does not require an in-depth how-to technical understanding of AI, but does require managerial curiosity and interest paired with firm, customer, and industry knowledge.

Second, the required technical AI skills need to be attained. In principle, managers have two options. Develop technical AI skills internally or acquire these skills from outside the firm. Interestingly, we found no difference in how leaders

approached skills scarcity compared with laggards.³³ We recommend a dual-sourcing strategy. Managers should develop existing internal skills *and* source external talent at the same time in order to build the necessary technical skill base to ensure efficient and effective application of AI technologies.

Finally, digital intelligence has to do with patience. AI is not an instant panacea. Our research unearthed rather lengthy, multiyear processes from project start to impactful execution. Just like the successful case that opened this article, AI projects are usually not deterministic from start to finish, but emerge as the project participants learn, and the system provides feedback. This also distinguishes AI projects from many other IT projects, where the end goal is the successful implementation and use of a system. Especially when embarking on an AI project for the first time, managers should allow the AI project team to experiment and provide them with a generous timeline to deliver results and sufficient funding, one of the main barriers we identified. This includes allowing for a “failure culture” as the team learns. DX leaders excelled at learning from failure and it helped them to reap more benefits from their AI projects.

In summary, managers are advised to start with an internal resources check before embarking on AI projects. This check should address questions such as “Do we have a digital strategy in place?” “Do we have the managerial and technical skills required to support successful digital transformation with AI? If not, how do we develop or acquire these skills?” “Are we willing and able to tolerate investing in an emerging rather than deterministic AI digital transformation journey, including accepting failure?”

Be Grounded

Following the insights derived from more than 7,000 projects worldwide, we conclude that firms are mainly applying the new digital technology to improve their existing business(es) (see Figure 3). The reported business impacts of the DX leaders also suggest a grounded approach with impacts such as improving the existing offering, increasing revenue, or enhancing operational efficiency (see Figure 6). Managers embarking on AI projects should take this insight as suggestive of a rather grounded approach to AI, at least initially. Rather than pursuing high-flying “pie-in-the-sky” projects, firms should “start small” with AI and base the project in their existing core business(es). Our opening case illustrated this: a focused application area and a relatively small project size. The setup allowed for early results, and the project setup was not made overly complicated. Again, this also points to the need for using AI for solving concrete business problems, rather than viewing it as radical innovation and business model disruption from the start—this may happen eventually, but later. AI, just as other technologies, is ultimately not about technology but business opportunities and capabilities. Only when enough experience has been accumulated should firms proceed to more difficult and complex projects involving innovation and new business models. This grounded approach also signifies that adopting AI is like adopting other new technology successfully. Start small, test, learn, and then

apply more widely. As we noted earlier in this article, this suggests that realizing the potential of AI requires the firm and the new technology to co-align for best application and impact, and it rejects the notion of technological or organizational imperatives.³⁴

Before embarking on AI projects, managers should conduct a reality check in terms of scope and intent of the project(s). This check should address questions such as “Are we experienced enough and resourced properly for the scope of the project?” “Are we following an incremental, current business focused approach with our DX/AI project(s)?” “Do we have a DX/AI projects roadmap?”

Be Integral

Successful firm-wide AI implementations require an integral, holistic approach. Being integral comes in six flavors: strategy, processes, data management, technology alignment, employee engagement, and culture.

As soon as AI leaves the experimental, feasibility-testing lab environment and is applied to a real business case, managers should first make sure it is embedded in and supportive of the firms’ digital strategy. The existence of a digital strategy separated the DX leaders from the laggards and signals the importance of viewing AI in a broader context. A firm’s digital strategy, which, in essence, outlines and documents how a firm wants to achieve its strategic objectives with the help of digital technologies—including but not exclusive to AI—channels its activities and provides for a guiding purpose.

Executing a digital strategy implies the “digitalization” of a firm’s core processes: from procurement processes to internal operations to customer engagement.³⁵ AI cannot augment analog processes. Managers should ask themselves how digital their firms’ core processes are. Our DX leaders’ analysis showed that digital processes significantly and strongly distinguished them from laggards.

AI requires data. As firms digitize their operations, thereby creating more digital data, the need for an integrated data management approach becomes vital. It is, therefore, not surprising that integrated data management was the number one organizational characteristic differentiating DX leaders from laggards, because the mere existence of a lot of data is good but not good enough. Data, even if sufficiently large, complete, consistent, accurate, and timely, are limited if they “live” in isolation and are not connected with other relevant data. Subscribing to the view that firms are essentially consumers, producers, managers, and distributors of information,³⁶ all their data should be connected and integrated to allow for maximum value capture and knowledge generation. To address this challenging task, some innovative firms have recently started to set up so-called data lakes, a centralized repository that allows them to store all their structured and unstructured data and access in a unified way. As firms employ AI for more complex, broader tasks and processes (say, enhancing customer experiences), integrated data management becomes more important. Enhancing customer experiences, for example, requires tapping into data from the firm’s ERP (Enterprise Resource Planning), CRM (Customer Relationship Management),

CMS (Content Management System), SMM (Social Media Monitoring), and other systems in order to ensure an integral approach to the customer journey.

Integrated data management requires technology alignment. Lack of it was one of the key barriers to AI success and successful alignment one of the key success factors we identified. Technology alignment specifically refers to the integration of new digital technologies, including AI, with a firm's existing technologies, and it is all about the question of whether the new and the old can "speak" together and "understand" each other in terms of data. For example, can the firm's legacy system provide the data required for an AI application in a format that it can compute? Managers should ensure that technology alignment is looked after and instruct experts to ensure seamless integration of the old with the new.

Last, integral implies managers should ensure employee engagement and a supportive culture. Successful AI thrives with engaged skilled staff and an enabling culture, both of which help to overcome internal resistance and lack of skills and knowledge, two of the key barriers we identified. Engagement is particularly important for the employees that will be impacted by AI. As firms seem to be particularly interested in applying AI in the creation of smart services (see Figure 3), for example, engaging and working with the service frontline employees will be instrumental to the success in smart services. Even though our research supports the augmentation view of AI, managers should be aware that frontline employees might fear displacement and should address this fear proactively. Research on how frontline employees' roles, responsibilities, and actions are likely to change due to AI-automated customer interfaces is in its infancy, but it is safe to assume that managers who address such inherent concerns proactively are more likely to achieve employee engagement.

In conclusion, managers are advised to think about AI as a broad means to support its company-wide digital transformation efforts. To ensure an integral approach, managers should address questions such as "Have our firm's core business processes been digitalized?" "Has our firm analyzed what existing/new offerings can benefit from DX/AI?" "Has our firm integrated all data into one single data repository?" "Is our firm's existing IT compatible with the DX/AI technology we plan to adopt?"

Be Teaming

Our opening case illustrated that going for AI alone is unlikely to lead to success. Just as Dr. Mayol and his colleagues collaborated with a technology adviser and provider, DX leaders stated support by technology partners as a key success factor, and the unavailability of support by a technology partner was stated as an implementation challenge by nearly 20% of firms. Teaming with one or several technology partners—which include technology generalists such as IBM or Fujitsu, software firms such as Microsoft or SAP, or consultancies such as Accenture or Deloitte³⁷—provides firms with two main advantages. First, it provides them with early access to new technology in a field that is still ill-defined and emergent. Second, it allows them to tap into the economies of scope

and project experiences that both technology firms and technology consultancies have accumulated over the past years as AI projects have mushroomed. For most firms, AI will, for the foreseeable future, not be an off-the-shelf product. Hence, teaming with technology partners to co-create a tailored AI solution is going to be the main approach for now.

The importance of teaming extends beyond the confines of working with technology partners and includes a firm's business ecosystem,³⁸ which includes suppliers, competitors, customers, and alliance partners from different industries. Having established an open innovation ecosystem was one of the organizational characteristics that set the DX leaders apart from the laggards. Open innovation ecosystems are a means to develop innovative offerings (products and services) beyond the internal capacity and capabilities of the firms. This approach recognizes that great talent often resides outside of a firm. Given the discussed AI technical skills scarcity, an open innovation ecosystems approach is particularly fruitful in the case of AI, and the DX leaders demonstrated this. Having established an Open Innovation Ecosystem was one of their defining characteristics. Generally, managers have two options: establishing their own ecosystem³⁹ or joining an existing one.⁴⁰ Often, as was the case with Dr. Mayol and his colleagues, the route to take is shaped by the nature of the collaboration with the technology partner(s).

Managers are advised to think about AI as an opportunity to partner and develop powerful ecosystems. To understand the teaming options, managers should address questions such as "Does our firm know with whom to partner in support of our DX/AI success?" "Does our firm know with whom competitors partner in their DX/AI projects?" "Did our firm develop or join an ecosystem to enhance its offerings?"

Be Agile

Organizational agility is both a key barrier and a key success factor according to our empirical analyses. Lack of it was the second most important AI implementation challenge, and great levels of organizational agility was the number one AI success factor. We found agility to also be one of the main business impacts of AI. Agility is, therefore, both a central AI success antecedent as well as an outcome of successful AI implementations, thereby reinforcing its importance as an antecedent. How can managers foster organizational agility? Organizational agility research suggests that a firm's ability to sense change and to respond readily to it by reconfiguring its resources, processes, and strategies is at the core of organizational agility.⁴¹ In the context of AI projects, this relates to flexibility in the way the project is approached and managed throughout its life cycle, as AI projects tend to be emergent rather than deterministic, as we noted earlier (cf. Be Intelligent).

Managers are advised to assess their company's agility in a realistic manner and implement corrective actions if needed. The following questions, guided by the logic of Singh et al.,⁴² are instructive: "Compared to our competition, how quickly and frequently are we adapting our processes and offerings to stay

competitive?” “Compared to our competition, how flexible are we to accommodating small, medium, and large changes to our processes and offerings?”

Lead

Managers should lead and actively endorse the firm’s AI project(s), just like Dr. Mayol at the Carlos Clinical Hospital in Madrid, and not relegate leadership to the project management level. We identified executive leadership as a key success factor and lack of leadership support as a key barrier. The DX leaders we analyzed demonstrated this fact forcefully. One of their defining organizational characteristics was a CEO who prioritized the firm’s digitalization efforts, including AI and other advanced digital technologies.

If data are the foundation for impactful AI, leadership provides the transformational energy for firms to be DIGITAL and, as a consequence, successful with AI. Notably, AI has several similarities with other technologies to be implemented in firms, and some of the aspects of our DIGITAL framework would relate to other change management projects as well. However, the broad nature of AI (requiring data, analyses, interdisciplinary teams) makes for some specific requirements, such as data, agility, and the teaming aspect.

Managers are advised to reflect honestly, “Is our executive team and middle management comfortable and supportive of the changes that DX/AI will bring to our firm?” “Is our executive team and middle management actively endorsing and continuously communicating the status and progress of our DX/AI activities to all stakeholders?”

Conclusion and Outlook

AI certainly holds a lot of promise but it is not a panacea. In order to reap its benefits, we developed DIGITAL as a guideline for AI success grounded in the empirical insights of close to 7,000 DX projects that involved new digital technologies such as AI. The basic approach of this article was to learn from today’s DX leader how to become the AI leader of tomorrow. At the same time, in line with the title of this article, we believe we can demystify a few aspects of AI.

The results of this study imply that, in many ways, AI is similar to other technologies companies adopt and implement. It certainly is typically deployed in digital transformation projects, and, as such, shares many similarities with other digital projects. At the same time, the focus on self-learning projects and long-run scaling comes with several interesting findings, such as the focus being integral, teaming, and agile. In contrast to press reports and also some academic papers, our approach to AI is a contemporary and realistic one. Before visions of “AI taking over everything” will become true, “realistic AI” will take place for a long time. It is and will be a competitive advantage to be quick and effective in AI, and our DIGITAL framework and the associated questions to managers should help overcome the barriers, but also some of the illusions, so that “realistic AI” will become real.

A question that we also addressed in the survey was the future role of humans in AI projects, which we do not report here in detail due to the controversial and nonconclusive nature of the responses, and the vastness of the topic. But overall, it is interesting that firms are positive about AI as a technology and the role of humans. First, they expect that AI and humans will work together in the future, rather than working against each other or replacing humans, for at least quite some time. Furthermore, managers assume that we will even see a human premium emerging in the future, in the sense that people will be paying more to get personal, human-to-human services rather than AI technology-mediated services. Interestingly, leaders and laggards are united in this view and showed no significant differences.

Acknowledgments

The authors wish to thank Fujitsu, Corporate Executive Officer and former Chief Marketing Officer Yoshiteru Yamada, and Manager Noriaki Tanaka for supporting the research project.

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Notes

1. For details regarding this case, see Instituto de Investigación Sanitaria Case Study (IdISSC), <https://www.youtube.com/watch?v=NIDNmwyMjAE>.
2. At present, to the best of our knowledge, no commonly agreed definition of artificial intelligence (AI) exists. Definitions range from "every aspect of learning or any other feature of intelligence . . . that a machine can be made to simulate" [John McCarthy, M.L. Minski, N. Rochester, and C.E. Shannon, "A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence," August 31, 1955, www-formal.stanford.edu/jmc/history/dartmouth.pdf] to "make computers do things at which, at the moment, people are better" [Elaine Rich and Kevin Knight, *Artificial Intelligence*, 3rd ed. (New York, NY: McGraw-Hill, 2009)] to "AI is whatever hasn't been done yet" [Douglas Hofstadter, *Gödel, Escher, Bach: An Eternal Golden Braid* (New York, NY: Basic Books, 1980)] to, more recently, "a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" [Andreas Kaplan and Michael Haenlein "Siri, Siri, in My Hand: Who's the Fairest in the Land? On the Interpretations, Illustrations, and Implications of Artificial Intelligence," *Business Horizons* 62/1 (January/February 2019): 15-25]. Given this, we purposely did not provide for an explicit definition of AI in our survey research. However, we provided application examples in the survey as illustrations of AI, such as call center transformation using advanced analytics and AI or transforming operations using Internet of things (IoT), advanced analytics, and AI. Generally, our investigation was guided by the broad and inclusive behavioral definition of AI as originally advanced by Brooks: "Artificial Intelligence . . . is intended to make computers do things, that when done by people, are described as having indicated intelligence" (Rodney Allen Brooks, "Intelligence

- without Reason," in *Proceedings of the 12th International Joint Conference on Artificial Intelligence*, ed. M. Ray and J. Reiter (Sydney, Australia: Morgan Kaufmann, 1991), pp. 569-595.
3. See, for example, Kartik Hosanagar and Apoorv Saxena, "The First Wave of Corporate AI Is Doomed to Fail," *Harvard Business Review Digital Articles*, April 18, 2017, <https://hbr.org/2017/04/the-first-wave-of-corporate-ai-is-doomed-to-fail>; Ben Taylor, "Why Most AI Projects Fail," *Artificial Intelligence*, March 1, 2018, <https://www.experfy.com/blog/why-most-ai-projects-fail>; Matthew Herper, "MD Anderson Benches IBM Watson in Setback for Artificial Intelligence in Medicine," *Forbes*, February 19, 2017, <https://www.forbes.com/sites/matthewherper/2017/02/19/md-anderson-benches-ibm-watson-in-setback-for-artificial-intelligence-in-medicine/#10c16c083774>.
 4. See, for example, Sam Ransbotham, David Kiron, Philipp Gerbert, and Martin Reeves, "Reshaping Business with Artificial Intelligence: Closing the Gap between Ambition and Action," *MIT Sloan Management Review*, September 6, 2017, <https://sloanreview.mit.edu/projects/reshaping-business-with-artificial-intelligence>.
 5. See, for example, Richard Waters, "Why We Are in Danger of Overestimating AI," *Financial Times*, February 4, 2018, <https://www.ft.com/content/4367e34e-db72-11e7-9504-59efdb70e12f>.
 6. Some of these cases are publicly accessible, examples include the following: <https://www.fujitsu.com/global/about/resources/case-studies/cs-2017nov-siemens-gamesa.html>; <https://www.youtube.com/watch?v=tpkQHlutSzo>; <https://www.youtube.com/watch?v=3LqQ6bjoip0>.
 7. This group of areas of AI business impact follows the logic of John Hagel III and Marc Singer, "Unbundling the Corporation," *Harvard Business Review*, 77/2 (March/April 1999): 133-141 (see Figure 1). The authors argued that most companies are essentially three kinds of businesses—a customer relationship business (customer interactions), a product innovation business (offerings), and an infrastructure business (operations).
 8. This research question was guided by the thinking behind the theory of the growth of the firm (Penrose), which attributes a key role to experiential knowledge. Edith T. Penrose, *The Theory of the Growth of the Firm* (London: Wiley, 1959).
 9. Hagel and Singer (1999), op. cit.
 10. The term *Triad* refers to the three key economic regions in the world (originally, the United States, Europe, and Japan) as originally coined by Ohmae [Kenichi Ohmae, *Triad Power: The Coming Shape of Global Competition* (New York, NY: Free Press, 1985)], though its modern understanding has broadened [e.g., Alan M. Rugman and Alain Verbeke, "A Perspective on Regional and Global Strategies of Multinational Enterprises," *Journal of International Business Studies*, 35/1 (2004): 3-18] to include North America, Asia, and Oceania.
 11. J. Scott Armstrong and Terry S. Overton, "Estimating Non-response Bias in Mail Surveys," *Journal of Marketing Research*, 14/3 (1977): 396-402. Armstrong and Overton suggest comparing early and late respondents for differences along key control variables, assuming that late respondents are more similar to nonrespondents. If no significant differences can be found, one can assume no significant response bias exists. We used the time stamps of the online surveys to gauge possible differences but found none.
 12. We derived the marker variable approach from Michael K. Lindell and David J. Whitney, "Accounting for Common Method Variance in Cross-sectional Research Designs," *Journal of Applied Psychology*, 86/1 (2001): 114-121. We compared the reported overall business impact of AI (see Figure 4a and 4b) with a theoretically unrelated measure added to the survey. The measure used concerned firms' United Nations Sustainable Development Goals focus. The two were unrelated ($r = -.046$; $R^2 = .003$), suggesting common method bias is not a major concern in our study.
 13. Sample details of the first survey, conducted in 2016-2017:
 Total sample size: $n = 1,614$ (firms).
 Regions: North Americas (Canada, United States) $n = 314$; Europe (Finland, France, Germany, Spain, Sweden, United Kingdom) $n = 520$; Asia (China, Indonesia, Japan, Singapore, South Korea, Thailand) $n = 674$; Oceania (Australia) $n = 106$.
 Industry split, North American Industry Classification System (NAICS) code: 23, 31-33, Manufacturing ($n = 427$); 51, Information ($n = 195$); 48-49, Transportation ($n = 56$); 41/42, 44-45, Retail ($n = 137$); 52, Financial Services ($n = 138$); 62, Healthcare ($n = 100$), other ($n = 661$).
 Firm size (employees): <100 full-time employees (FTEs; $n = 0$); 100-499 ($n = 499$); 500-999 ($n = 414$); 1,000-4,999 ($n = 440$); 5,000+ ($n = 261$).

Firm size (revenue): <1M\$ ($n = 4$); 1-10M\$ ($n = 182$), 10-100M\$ ($n = 581$); 100-1Bn\$ ($n = 561$); 1Bn\$+ ($n = 263$).

Respondent characteristics:

Gender: Female (24%), Male (76%).

Age: 20s ($n = 147$), 30s ($n = 515$), 40s ($n = 418$), 50s ($n = 303$), 60s ($n = 161$).

Position: C-suite ($n = 1,023$), \times VP-level ($n = 591$), Manager ($n = 0$).

Sample details of the second survey, conducted in 2017-2018:

Total sample size: $n = 1,535$ (firms).

Regions: North Americas (Canada, United States) $n = 137$; Europe (Finland, France, Germany, Spain, Sweden, United Kingdom) $n = 502$; Asia (China, Indonesia, Japan, Singapore, South Korea, Thailand) $n = 473$; Oceania (Australia, New Zealand) $n = 106$.

Industry split, NAICS code: 31-33, Manufacturing ($n = 280$); 51, Information ($n = 93$); 48-49, Transportation ($n = 83$); 41/42, 44-45, Retail ($n = 472$); 52, Financial Services ($n = 158$); 62, Healthcare ($n = 132$), other ($n = 0$).

Firm size (employees): <100 FTEs ($n = 9$); 100-499 ($n = 309$); 500-999 ($n = 348$); 1,000-4,999 ($n = 357$); 5,000+ ($n = 195$).

Firm size (revenue): <1M\$ ($n = 9$); 1-10M\$ ($n = 157$), 10-100M\$ ($n = 425$); 100-1Bn\$ ($n = 406$); 1Bn\$+ ($n = 205$).

Respondent characteristics:

Gender: Female (35%), Male (65%).

Age: 20s ($n = 173$), 30s ($n = 474$), 40s ($n = 332$), 50s ($n = 171$), 60s ($n = 68$).

Position: C-suite ($n = 931$) \times VP-level ($n = 262$), Manager ($n = 25$).

14. Other technologies used were, for example, security technologies, mobile technologies, blockchain, cloud computing, IoT, and big data analytics. The definition for digital transformation used was "Digital transformation refers to the integration of advanced digital technologies (AI, IoT, and cloud-based services) into significant areas of a business with the aim of changing how the business operates and how value is delivered to and created with customers."
15. For details on smart offerings, see, for example, Michael E. Porter and James E. Heppelmann, "How Smart, Connected Products Are Transforming Companies," *Harvard Business Review*, 93/10 (October 2015): 96-114.
16. The effect size for smart services was Cohen's $f = .121$, and for manufacturing automation Cohen's $f = .142$.
17. The numerical difference in the range of firms is a reflection of missing values.
18. Factors examined include industry sector, country, firm characteristics (revenue, number of employees, digital/traditional), and respondent characteristics (gender, age, title/position).
19. In the information technology (IT) literature, this co-evolutionary view is referred to as the emergent imperative. M. Lynne Markus and Daniel Robey, "Information Technology and Organizational Change: Causal Structure in Theory and Research," *Management Science*, 34/5 (May 1988): 583-598.
20. We derived this insight from digital transformation projects involving AI of one of the author's employers, a global provider of IT services, practitioner interviews, and the literature, such as Amir Sharif, "Harnessing Agile Concepts for the Development of Intelligent Systems," *New Generation Computing*, 17/4 (December 1999): 369-380; Antonio Gulli, *TensorFlow 1.x Deep Learning Cookbook: Over 90 Unique Recipes to Solve Artificial-intelligence Driven Problems with Python* (Birmingham, UK: Packt Publishing, 2017); Nicolas Seydoux, Khalil Drira, Nathalie Hernandez, and Thierry Monteil, "Reasoning on the Edge or in the Cloud?" *Internet Technology Letters* 2/1 (January/February 2018): e51.
21. See, for example, Jian-hua Li, "Cyber Security Meets Artificial Intelligence: A Survey," *Frontiers of Information Technology & Electronic Engineering*, 19/12 (December 2018): 1462-1474.
22. See, for example, Francisco J. Mata, William L. Fuerst, and Jay B. Barney, "Information Technology and Sustained Competitive Advantage: A Resource-based Analysis," *MIS Quarterly*, 19/4 (December 1995): 487-505; Ferdinand Mahr, *Aligning Information Technology, Organization, and Strategy: Effects on Firm Performance* (Wiesbaden: Gabler, 2010).
23. Obviously, given the cross-sectional nature of our survey, we cannot claim any causal links here. AI leaders might exhibit stronger digital skills as a result of their digital transformation efforts, and/or their stronger digital skills resulted in more advanced digital transformation efforts compared with the other firms.

24. We defined digital natives as firms that were less than 15 years old at the time of the survey and marketing their offerings (products and services) purely online. The survey included a total of $n = 648$ digital natives.
25. For the majority of firms (61%), it took one or more years before outcomes could be delivered. For 23% of firms, it took two or more years, and for 9%, three or more years.
26. Small effect size for industry, Cramer's $V = .037$.
27. Small effect size for revenue, Cramer's $V = .054$, and for employees, Cramer's $V = .071$.
28. Throughout our DX leader analysis, we report both statistical significance and effect sizes. Effect sizes are estimates of the strength of an effect in a given population. Especially when sample sizes are large, like in our studies, inferential tests become oversensitive and even the smallest of effects turn out to be statistically significant. In such cases, statistical significance is actually *insignificant* and what matters more is the found effect size. Cf. Jürgen Kai-Uwe Brock, "The 'Power' of International Business Research," *Journal of International Business Studies*, 34/1 (January 2003): 90-99. As we display in Figures 5, 6, and 8, the effects we found are medium to large according to Cohen's effect size classification. Jacob Cohen, *Statistical Power Analysis for the Behavioral Sciences*, 2nd ed. (Hillsdale, NJ: Lawrence Erlbaum, 1988). Compared with other studies in the field of international business and organization research (we use the effect size reviews of Ellis (2010) and Paterson et al. (2015) as benchmarks and visualized the average effect sizes they found in Figures 5, 6, and 8), the effects we found were stronger for all but one effect, indicating substantial practical relevance for managers. Paul D. Ellis, *The Essential Guide to Effect Sizes: Statistical Power, Meta-Analysis, and the Interpretation of Research Results* (Cambridge: Cambridge University Press, 2010); T.A. Paterson, P.D. Harms, P. Steel, and M. Credé, "An Assessment of the Magnitude of Effect Sizes: Evidence From 30 Years of Meta-Analysis in Management," *Journal of Leadership & Organizational Studies*, 23/1 (February 2016): 66-81.
29. The found effect sizes were $\phi = .086$, $\phi = .093$, and $\phi = .077$, respectively.
30. Nicola Jones, "Computer Science: The Learning Machines," *Nature*, 505/7482 (January 8, 2014): 146-148.
31. Chen Sun, Abhinav Shrivastava, Saurabh Singh, and Abhinav Gupta, "Revisiting Unreasonable Effectiveness of Data in Deep Learning Era," *arXiv:1707.02968*, July 2017.
32. See, for example, David Cyranoski, "China Enters the Battle for AI Talent," *Nature*, 553/7688 (January 17, 2018): 260-261.
33. 51% of DX leaders developed skills internally, and 49% sourced skills externally versus 52% and 48% for laggards; χ^2 value = .011, p value = .915 in a 2×2 table.
34. As discussed by Markus and Robey, the technological imperative implies that technology is an exogenous force, which deterministically shapes organizations and people. M. Lynne Markus and Daniel Robey, "Information Technology and Organizational Change: Causal Structure in Theory and Research," *Management Science*, 34/5 (May 1988): 583-598. The organizational imperative, in contrast, argues that organizations and people have almost unlimited choice over technological options and control over its consequences. As illustrated in our opening case, successful applications of AI in organizations are neither following the technological imperative nor the organizational imperative, but the emergent imperative, which holds that the uses and consequences of a technology in an organization cannot ex ante be fully determined but emerge from complex social interactions within the firm and its ecosystem.
35. See, for example, Gerrit Berghaus, René Kessler, Viktor Dmitriyev, and Jorge Marx Gómez, "Evaluation of the Digitization Potentials of Non-digital Business Processes," *HMD Praxis der Wirtschaftsinformatik*, 55/2 (April 2018): 42c444.
36. See, for example, Kenneth J. Arrow, *The Limits of Organization* (New York, NY: W.W. Norton, 1974); Arthur L. Stinchcombe, *Information and Organizations* (Berkeley: University of California Press, 1990).
37. The main technology partners our research identified were, in alphabetical order: Accenture, Amazon, Capgemini, Cisco, Dell, Deloitte, Fujitsu, Google, Hewlett Packard Enterprise (HPE), Hitachi, IBM, Microsoft, NEC, NTT Data, Oracle, PwC, SAP, Salesforce, and TCS (Tata Consultancy Services).
38. The view of a business ecosystem goes back to Moore, who argued that "a company be viewed not as a member of a single industry but as part of a business ecosystem that crosses a variety of industries. In a business ecosystem, companies coevolve capabilities around a new innovation: they work cooperatively and competitively to support new products, satisfy

- customer needs, and eventually incorporate the next round of innovations.” James F. Moore, “Predators and Prey: A New Ecology of Competition,” *Harvard Business Review*, 71/3 (May/June 1993): 75-86.
39. See, for example, Henry Chesbrough, Sohyeong Kim, and Alice Agogino, “Chez Panisse: Building an Open Innovation Ecosystem,” *California Management Review*, 56/4 (Summer 2014): 144-171; René Rohrbeck, Katharina Hölzle, and Hans Georg Gemünden, “Opening Up for Competitive Advantage—How Deutsche Telekom Creates an Open Innovation Ecosystem,” *R&D Management*, 39/4 (September 2009): 420-430.
 40. For the open innovation dimension of business ecosystems, see Henry W. Chesbrough, *Open Innovation: The New Imperative for Creating and Profiting from Technology* (Boston, MA: Harvard Business School Press, 2003).
 41. See, for example, Carmen M. Felipe, José L. Roldán, and Antonio L. Leal-Rodríguez, “An Explanatory and Predictive Model for Organizational Agility,” *Journal of Business Research*, 69/10 (October 2016): 4624-4631.
 42. Jagdip Singh, Garima Sharma, James Hill, and Andrew Schnackenberg, “Organizational Agility: What It Is, What It Is Not, and Why It Matters,” *Academy of Management Proceedings*, 2013/1 (2013): 11813-11813.